

National Aeronautics and Space Administration

Investigation of Spiking Neural Networks for Modulation Recognition using Spike-Timing-Dependent Plasticity

Eric J. Knoblock, NASA GRC Hamid R. Bahrami, The University of Akron

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- Motivation and Goals
- Overview of Spiking Neurons
- Spiking Neuron Model
- SNN Architecture
- Learning Algorithm
- Classification Error Performance
- Discussion and Future Work



- NASA's infusion of new capabilities
 - Machine learning and artificial intelligence
 - Increased mission science return, enhanced autonomy
- Spiking Neural Networks (SNNs) and neuromorphic hardware
 - Energy efficiency
 - Ideal for resource-constrained platforms
 - CubeSats
- Cognitive functionality
 - Modulation recognition capability (BPSK, QPSK, 8PSK)
 - SNN using STDP
 - Classification error performance



- SNNs model biology
- Neurons and connecting synapses
- Neuron membrane potential and threshold
- Action potentials (e.g., spikes)
- Neuronal Refractoriness







 Leaky Integrate and Fire (LIF) Model

 $\tau \, d\nu/dt = -\nu(t) + RI(t)$

• Simplified Response Model (SRM)

$$v_t = v_{t-1} + \sum_i \omega_i s_{it} - D$$











- Unsupervised learning
- Spike-Timing-Dependent Plasticity (STDP)
- Correlation of pre- and postsynaptic spike arrivals

 $\Delta \omega (\Delta t) = \begin{cases} A_+ \exp{(\Delta t/\tau_+)}, \ \Delta t < 0 \\ A_- \exp{(-\Delta t/\tau_-)}, \ \Delta t \ge 0 \end{cases}$

- Adaptive membrane potential
- Lateral inhibition



Training Patterns



Learned Patterns









- SNN model for modulation recognition
 - Compare with CNN implementation
- Data set
 - More extensive samples with noise
 - Actual sampled I-Q values
- Learning methods
 - Challenges of unsupervised learning
 - Other STDP variants
 - Supervised, reinforcement methods
- Neural network architectures
 - Deep learning
 - Recurrent vs feedforward
- Implementation on neuromorphic hardware



Thank you